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AFAL-TR-75-103

INTEGRATION TECHNOLOGY PROGRAM
FINAL SUMMARY REPORT

THE ANALYTIC SCIENCES CORPORATION

Technical Report AFAL-TR-75-103

Final Report for Period July 1972 - March 1975

June 1975

Distribution is limited to U.S. Government Agencies only, Test and Evaluation, June 1975. Other requests for this document must be referred to AFAL (RWM-666A), WPAFB, Ohio 45433

Air Force Avionics Laboratory
Air Force Systems Command
Wright-Patterson Air Force Base
Ohio 45433

NOTICE

This technical report has been reviewed and is approved for publication.

FOR THE DIRECTOR

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This document summarizes the work performed from July 1972 through March 1975 under Contract No. F33615-72-C-1787, Advanced Development Program 666A, Task Number 2, with the Air Force Avionics Laboratory, by The Analytic Sciences Corporation (TASC), 6 Jacob Way, Reading, Massachusetts 01867. The report was submitted on 30 April 1975 as TR-316. The work described in this report was performed by several individuals from TASC whose

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19. oscillators, reduced-order estimators, system integration, time standards.

20. names appear in the referenced documents. The authors acknowledge the assistance of the Air Force Project Engineers, Major Stephen Schwam and Captains Harvey T. Brock, Jr., and Robert Warzynski (AFAL/RWM-666A), and Mr. Jerry Covert (ESD).

FOREWORD

This document summarizes the work performed from July 1972 through March 1975 under Contract No. F33615-72-C-1787, Advanced Development Program 666A, Task Number 2, with the Air Force Avionics Laboratory, by The Analytic Sciences Corporation (TASC), 6 Jacob Way, Reading, Massachusetts 01867. The report was submitted on 30 April 1975 as TR-316. The work described in this report was performed by several individuals from TASC whose names appear in the referenced documents. The authors acknowledge the assistance of the Air Force Project Engineers, Major Stephen Schwam and Captains Harvey T. Brock, Jr., and Robert Warzynski (AFAL/RWM-666A), and Mr. Jerry Covert (ESD).

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1. INTRODUCTION

The Integration Technology Program has focused attention on the complex issues associated with the integration of aircraft multisensor (or hybrid) navigation systems. A digital computer is the central element of a typical multisensor integrated navigation system, as shown in Fig. 1. The computer performs the "dedicated" data processing specifically related to individual sensors and displays, plus the processing of algorithms required to make the individual sensors "play together", i.e., the sensor integration computations. The Integration Technology Program has placed maximum emphasis on the problems associated with the design of these sensor integration algorithms.

The class of algorithms which have come to be known as Kalman filters have attained rapid popularity for sensor integration. This popularity is due to the potentially large performance improvement derived from the "optimal" mixing of sensor data provided by the Kalman filter. However, several difficulties are encountered in the practical implementation of Kalman filters (Ref. 1). These difficulties, each of which is addressed in depth by the Integration Technology Program, are broadly categorized as follows:

- Sensor Modeling - Kalman filters require dynamical and statistical error models of the sensors. If these models are "inexact," Kalman filter performance is degraded.

- Computational Constraints - Because an exact error model for the sensors of hybrid navigation systems cannot be realized in a

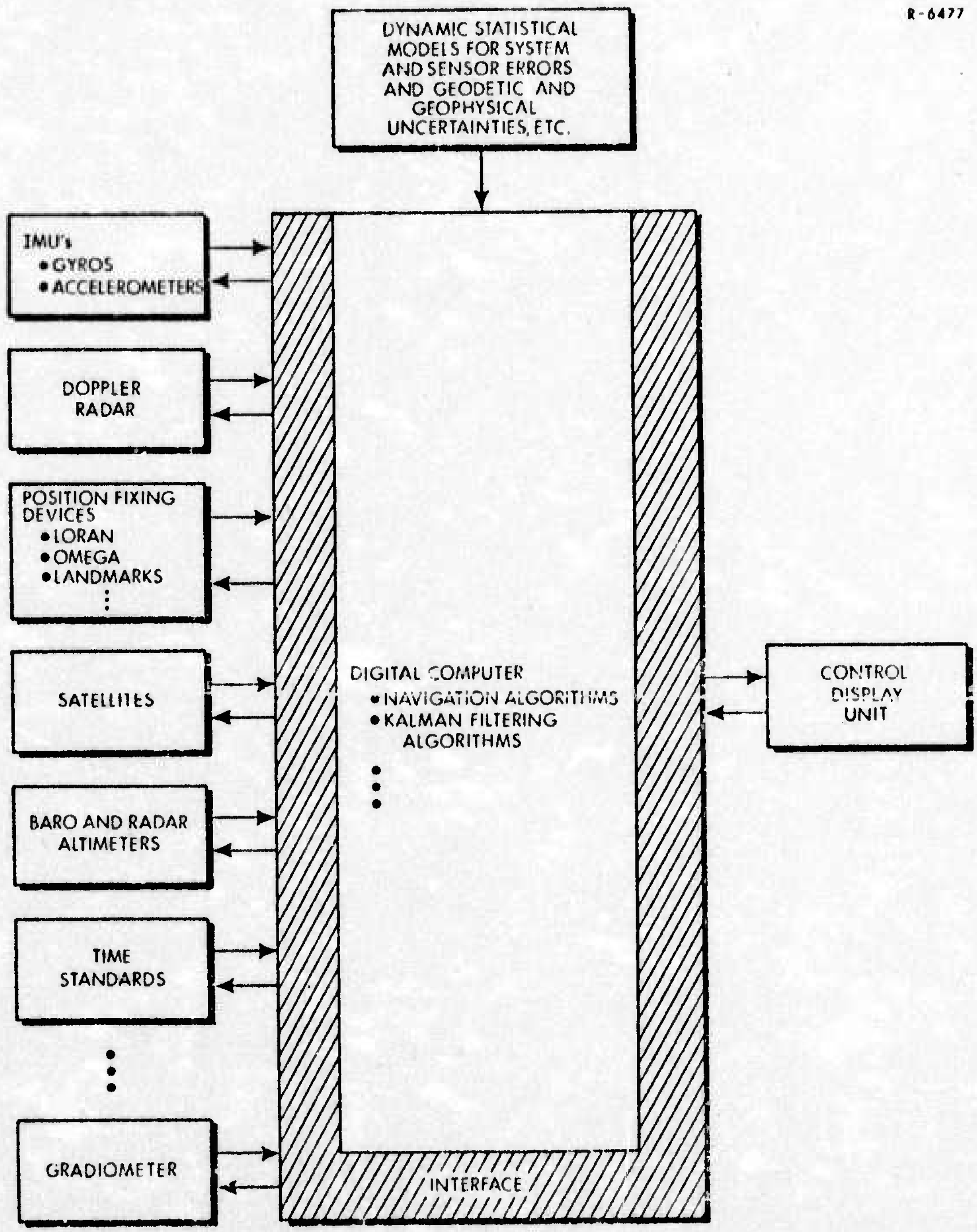

Figure 1 Typical Multisensor (Hybrid) Integrated Navigation System

> finite computer, approximations must be made. If great care is not taken in choosing these approximations and evaluating the compatibility of Kalman filters based thereon with real sensor performance, filter performance degradation is again experienced.

The Integration Technology Program has made significant technical advances in these areas, by providing systematic approaches to sensor modeling and Kalman filter design. In addition, several specific navigation system designs have been analyzed, utilizing the evaluation methodology developed under the Integration Technology Program.

The overall objective of the work summarized herein is to further develop the Air Force's capability to design and evaluate multisensor aircraft navigation systems in a meaningful and cost-effective manner. The development of this capability was addressed in terms of the perspective and analytical techniques offered by the powerful state-space concepts of modern estimation theory (Kalman filtering) in suitably modified form. The work involved:

- Sensor Error Model Development - Utilization of sensor test data, collected and assembled in a Sensor Data Bank, to develop and validate sensor error models.
- Analytical Evaluation - A systematic and applications-oriented design and evaluation methodology.
- Advanced Techniques - Investigation of advanced system integration and analysis techniques.

This report is intended to serve as a guide to the differing activities encompassed by the Integration Technology Program. A brief summary of the work performed will be presented here, with appropriate references to the detailed

technical reports prepared under the Integration Technology Program. The organization of this report relative to the work performed is given in Fig. 2.

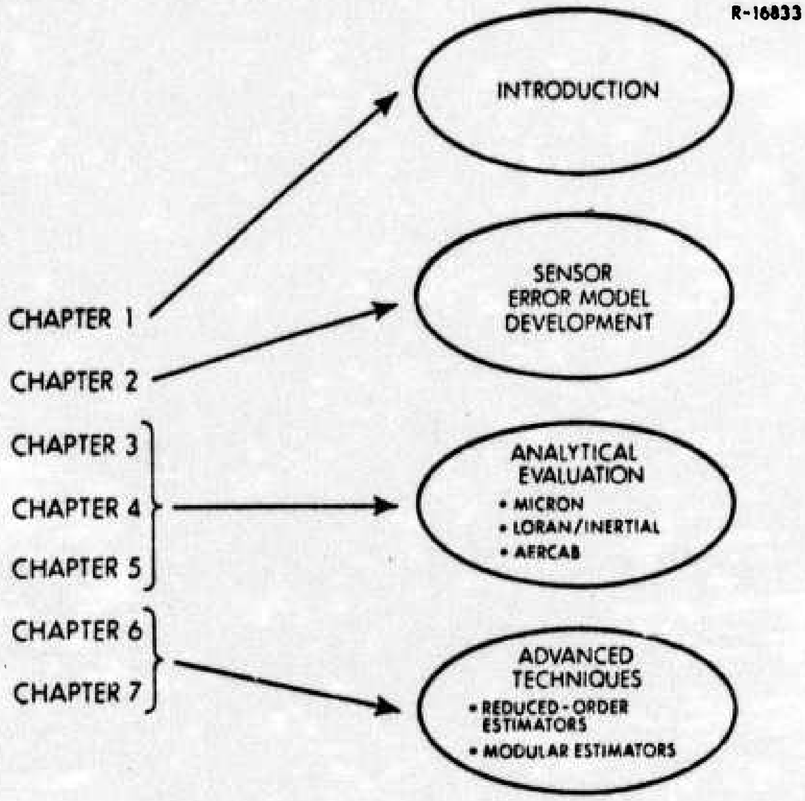

Figure 2 Organization of the Report

2. SENSOR ERROR MODEL DEVELOPMENT

One aspect of the Integration Technology effort was a technology demonstration of sensor error modeling based upon data available from laboratory and operational tests. As depicted in Fig. 3, in order to design systems and predict their performance, it is absolutely necessary to make assumptions (i.e., develop models) concerning the physical nature of sensors. In fact, in multisensor navigation systems, the designed software (e.g., the Kalman filter equations) is based totally on models reflecting the assumed nature of the real world. Unavoidably then, assumptions in the form of models must be made. The utilization of sensor test data in the modeling process has provided insight into the behavior of the devices of interest in an operational environment.

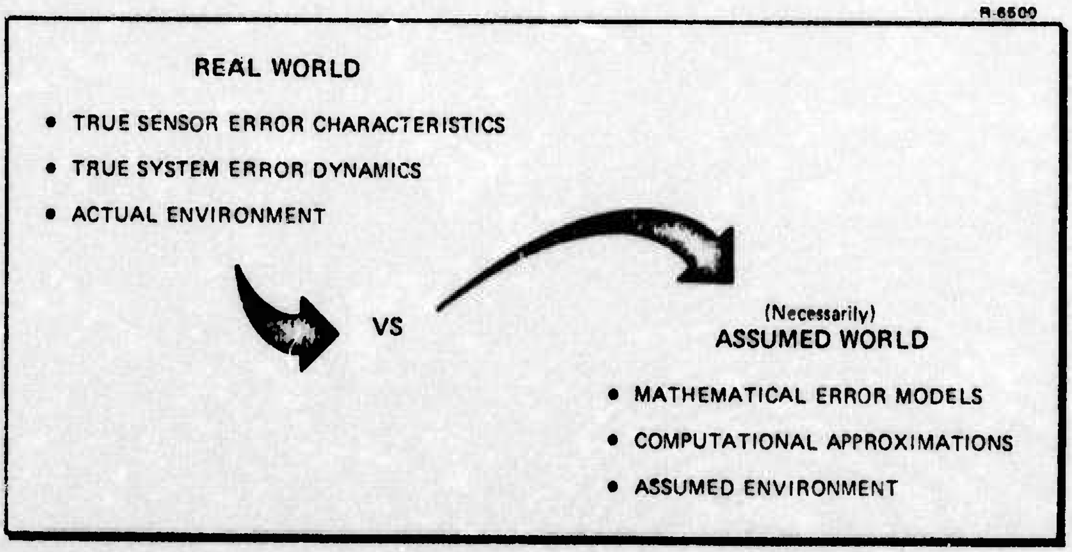

Figure 3 The Underlying Problem in Modeling

To aid in the storage and retrieval of sensor test data for error modeling purposes, the Sensor Data Bank was established. The Sensor Data Bank is a computerized test data storage structure combined with associated procedures which allow:

- Input handling
- Editing
- Correction
- Storage
- Retrieval
- Output
- Data consolidation

These features provide ease of access to the sensor test data for use in error model development.

2.1 INERTIAL SENSOR ERROR MODELING

Reference 2 describes the development of a prototype data handling and storage structure to be used as an aid in the determination of error models for the AN/ASN-90 IMU. The overall structure of the Sensor Data Bank was designed as a complete, unified and efficient repository for test data obtained from both the system manufacturer and government test facilities. The general character of the individual test data files, which comprise the Sensor Data Bank, allow them to accommodate a wide range of test results with ease of access to and retrieval of any portion or all of the stored test data. The data files may be expanded in size, with a minimum of effort, to incorporate additional test data that was either unavailable or not of interest at the time the initial data file was created. These features are beneficial in the determination of error models.

Error models were developed for all parameters of interest for which USAF test data was available. One benefit of the error modeling portion of the work was to observe gyro thermal transient drifts which differ from those previously published by the manufacturer. A covariance analysis of a local level mechanization of the AN/ASN-90 system demonstrated that this type of mismodeling can be a major contributor to degraded alignment of the IMU (see Fig. 4) and subsequent weapon delivery accuracy.

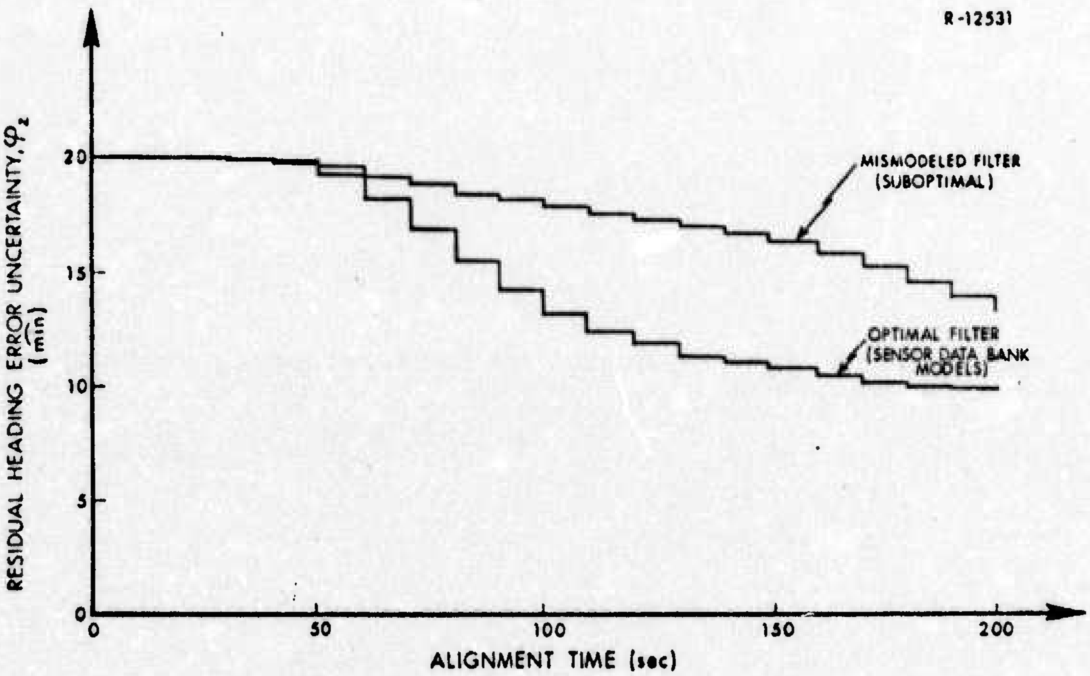

Figure 4 Heading Error During Alignment

The results obtained during the development and use of the AN/ASN-90 Test Data File of the Sensor Data Bank led to:

- A better knowledge of the behavior of the AN/ASN-90 IMU under field conditions and maintenance

- An improved and more efficient method of determining error models from large samples of actual test data

- A new model for the gyro thermal transient drift parameter which is important in the alignment of the AN/ASN-90 IMU and subsequent navigation performance

- Realization of long-term gyro bias drift repeatability magnitudes which are larger than previous models and which demand calibration during system operation.

2.2 TIME STANDARD ERROR MODELING

The increased accuracy of modern navigation systems has led to a number of applications for precision time and frequency standards. Synchronized multistation electronic navigation systems (e.g., Loran, OMEGA) can be used in a direct ranging mode rather than the conventional hyperbolic configuration if the user navigation system includes an accurate onboard time source or standard. A source of precise time in the user receiver is essential for the proper interpretation of signals from a satellite-based radio navigation system such as the NAVSTAR Global Positioning System (GPS).

The increased number of applications for precision time standards has created a need for time standard error models which accurately reflect the behavior of these precision devices. Reference 3 describes the development of time standard error models, for use in multisensor navigation systems, utilizing the Sensor Data Bank. Emphasis has been placed upon both quartz crystal oscillators and the two most common atomic frequency standards, the rubidium gas cell and cesium beam devices. The approach taken in the error model

development included: 1) an investigation of the fundamental physical processes involved in the operation of the various devices and 2) evaluation of the actual performance of the devices, as determined from the time standard test data included in the Sensor Data Bank.

An important tool which relates the observed time domain behavior to the underlying noise processes is the two-sample Allan variance defined as

$$\sigma_y^2(\tau) \equiv \left\langle \frac{(\bar{y}_{k+1} - \bar{y}_k)^2}{2} \right\rangle \qquad (1)$$

where $\langle\cdot\rangle$ denotes infinite time average and

$$\bar{y}_k \equiv \frac{1}{\tau}\int_{t_k}^{t_k+\tau} y(t)\,dt, \qquad t_{k+1} = t_k+\tau,\ k=0,1,2\ldots \qquad (2)$$

is the average frequency error over the averaging interval τ. From an Allan variance analysis of time standard test data, both the type and intensity of the various perturbing noise processes in the standard can be determined. Another benefit of the Allan variance is that it provides a time domain characterization of flicker noise which is observed in all the time standards of interest. To provide for a more realistic description of time standard performance, a time domain flicker noise model was developed. The model is an approximation, but any arbitrary degree of precision in the approximation can be obtained by increasing the size (number of states) of the model.

The validity of the resultant time standard error models (including the modeling of flicker noise effects) was verified for a representative sample of the time standard test data available. The model validation was effected by

treating the test data as measurement data in a Kalman filter which, in turn, was based upon the derived error models. This procedure is outlined in Fig. 5. The resultant filter behavior provided insight into the validity of the error models.

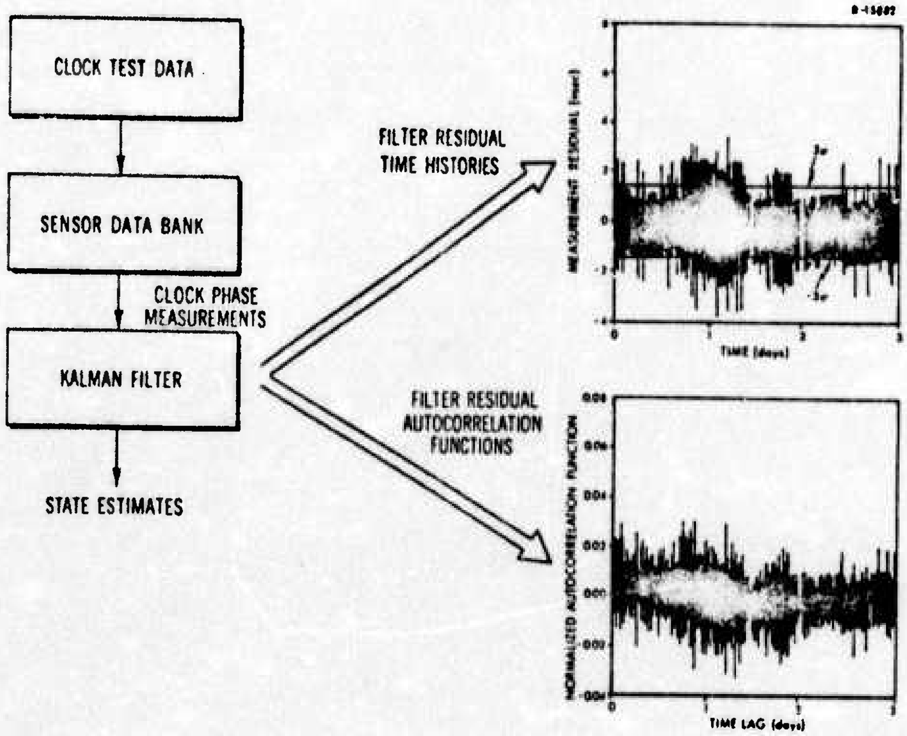

Figure 5 Clock Model Validation Procedure

The work described in Ref. 3 resulted in:

- The initiation of a time standard data bank
- An increased knowledge of the noise processes in time standards and associated methods of analysis
- The development of a time domain model of flicker noise
- A set of time standard error models applicable to navigation system analyses and operational software, verified to the extent possible with available test data representing the performance of actual devices.

3. MICRO-NAVIGATOR (MICRON) ANALYSIS

A strapdown micro-navigator (MICRON) is presently under development by AFAL/Autonetics for applications requiring a small, reliable, moderately accurate inertial navigator. The attitude sensors in MICRON will consist of two Micro-Electrostatic Gyroscopes. As part of the development of MICRON, a strapdown inertial navigator designated as N57A has been fabricated and tested. This system uses three accelerometers for measuring specific force and two Micro-Electrostatic Gyros (MESG) for maintaining an inertial reference. The N57A is intended to demonstrate MICRON's function and performance, but not MICRON's ultimate small size.

TASC has been conducting analytic studies in support of the MICRON development program since March 1971 in the areas of MESG error modeling, system calibration, simulation and test support (Refs. 4 through 8). Under the current contract, efforts have been directed at development of a unified calibration technique for the MESG and at system performance simulations and test support. Separate reports (Refs. 7 and 8) have been prepared to discuss the results of these two MICRON analysis investigations.

3.1 UNIFIED CALIBRATION DEVELOPMENT

The error sources of the MESG, namely gyro drift rate and spin axis attitude readout error, are well-defined

processes for which analytical models have been developed (Refs. 4 and 5). The MESG error models are used for gyro compensation during system operation. The MESG calibration process determines the coefficients of these models.

The existing Autonetics calibration procedure, shown schematically in Fig. 6, consists of taking two sets of data and evaluating the drift rate and attitude readout (ARO) error coefficients separately. Each set of coefficients is then used to improve the estimates of the other set in an iterative procedure until no further improvement is realized. This calibration technique requires approximately 10 hours of data collection and two separate computer programs.

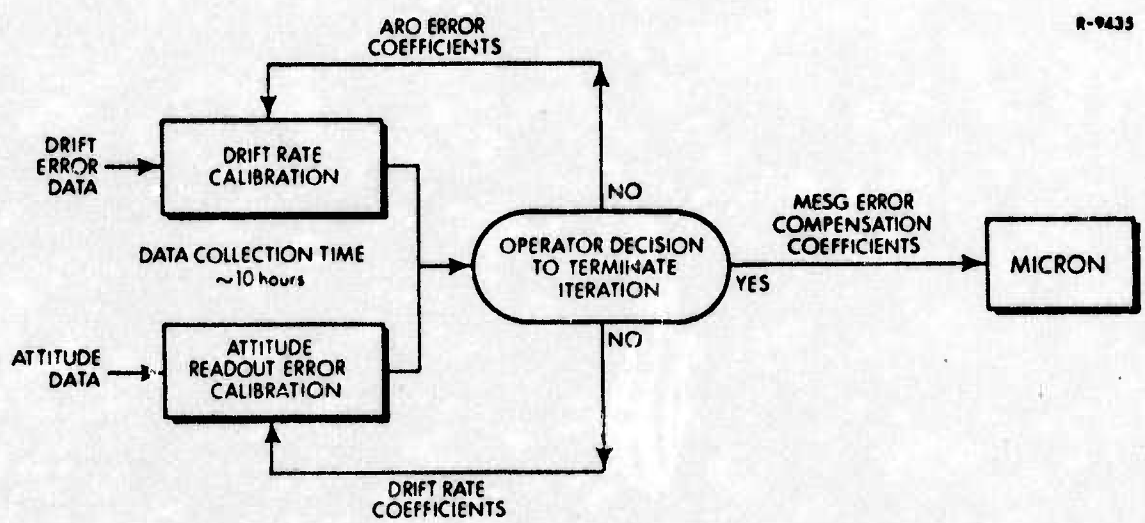

Figure 6 Existing MESG Calibration Technique

The work that has been performed in the development and evaluation of a proposed unified calibration algorithm (UNICAL) is described in Ref. 7. UNICAL, shown schematically in Fig. 7, will require only one set of data, taking about 5 hours to collect, and one computer program to estimate all the drift rate and attitude readout error coefficients.

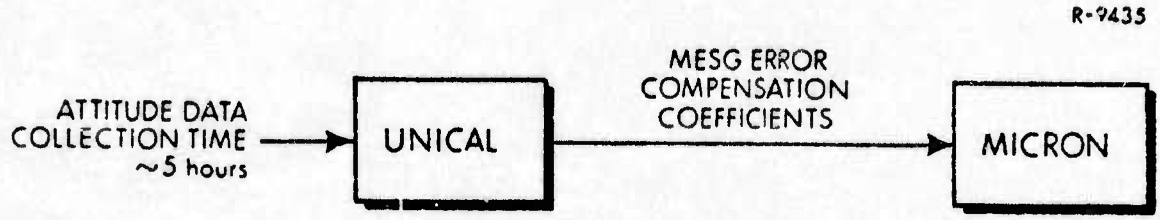

Figure 7 Proposed MESG Calibration Technique (UNICAL)

During this study a computer program was generated to implement the UNICAL technique for a reduced state-size set of gyro drift rate and ARO error models. The reduced state-size MESG models were a subset of the full drift rate and ARO error models selected to include the principal error mechanisms and enough of the nonlinearities to indicate the problems that they might present and yet be small enough to manageably conduct UNICAL development investigations. Covariance analysis and "synthetic" data calibration studies were performed on these reduced state models to assess the potential of the UNICAL technique.

The covariance analysis results, although they are only approximate since UNICAL is a nonlinear filter, provided an indication of the amount of data required to attain satisfactory calibration. These results indicated that between one and three hours of data collecton would be required, depending on the level of noise on the measurements. A brief investigation into the effect of the magnitude of the initial covariance matrix was made. These covariance analysis results yield optimistic performance indications because no consideration of the linearization errors is included.

The synthetic data calibration studies progressed in two steps. The UNICAL filter was tuned to synthetically generated calibration data with one set of MESG model coefficients. Synthetic calibration data was then generated under similar

conditions using MESG model coefficients chosen to represent the available data on N57A-type gyros. This data was used to evaluate the performance of the UNICAL technique. Figures 8 and 9, which present the results of the synthetic data studies, show the rms drift rate and ARO residuals as a function of the number of measurements processed by the UNICAL algorithm.

The principal results of this synthetic data analysis of UNICAL are:

- Residual ARO error can be reduced to within specification in approximately 100 measurements.
- It was estimated that approximately 1100 data points, taking 5½ hours to collect, would be required to reduce the residual drift rate to specification.
- A filter startup problem was identified.
- Fictitious process noise must be added to certain model states to avoid filter divergence problems.
- Correlation coefficients were determined for the estimate errors of all the model states.

The data requirement estimates resulting from the synthetic data analysis assumed that the best apriori estimate for each MESG model state was zero, that the standard deviation of the white noise on the measurement was 1.0×10^{-5} rad, and that the initial error in the estimate of the rotor spin axis vector was small.

3.2 SIMULATION AND TEST SUPPORT STUDIES

A set of system level analyses that have been conducted to support the development of MICRON is documented in

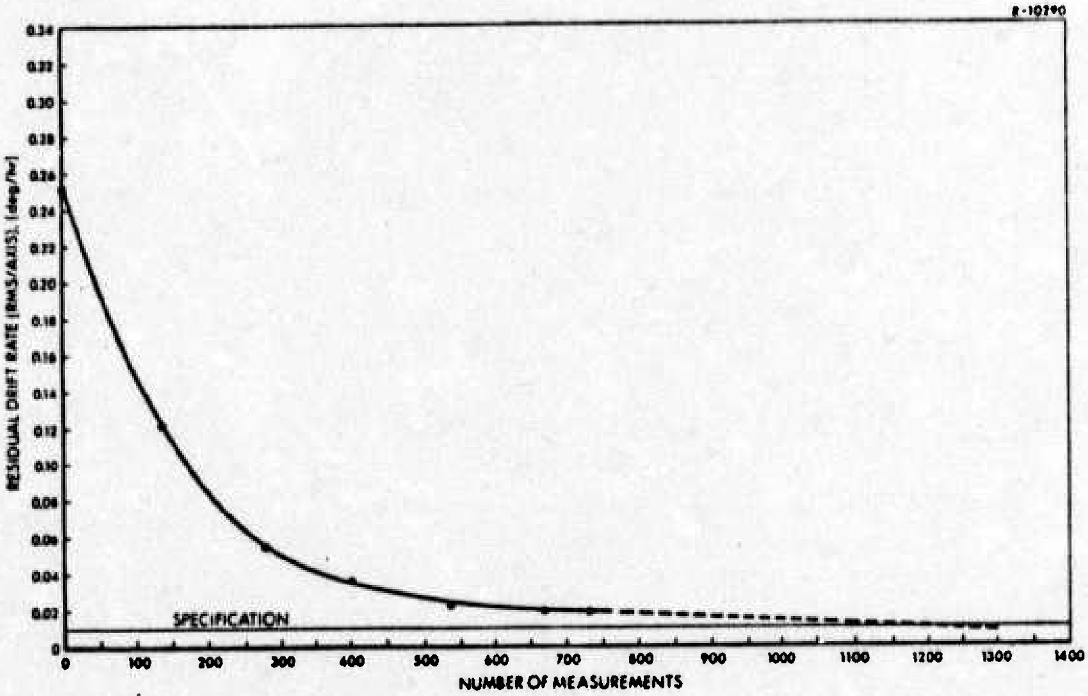

Figure 8 RMS Drift Rate Residual vs Number of Measurements (UNICAL Synthetic Data Calibration)

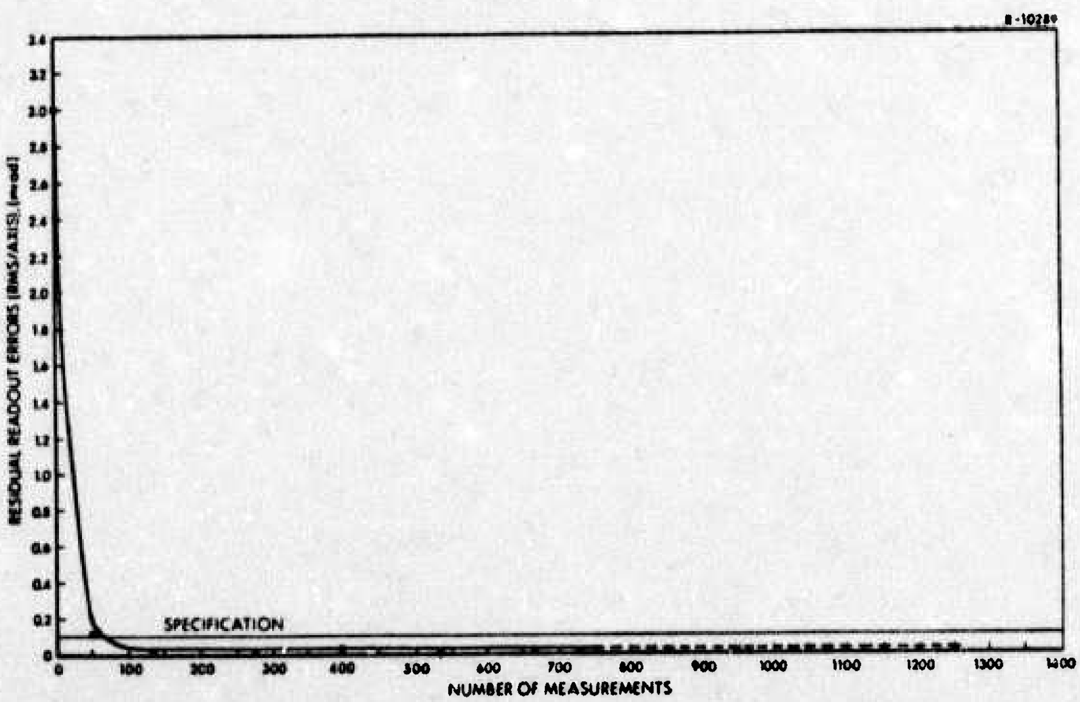

Figure 9 RMS Attitude Readout Residual vs Number of Measurements (UNICAL Synthetic Data Calibration)

Ref. 8. These studies consisted of:

- Exercising the previously developed MICRON Computer Simulation Program (MCSP) to evaluate the effects of MESG instrument variations and severe environments on navigation performance.

- Developing models to describe the propagation of instrument errors into navigation system errors and generating a covariance analysis computer program to conduct statistical performance predictions for MICRON.

- Supporting the test program of the N57A demonstration system by reviewing the Test Plan developed by Autonetics and by evaluating the laboratory and van test data.

The MCSP studies investigated the effects on MICRON performance of reducing the preload charge level on the MESG's, eliminating the instrument turn-on repeatability error, and subjecting the system to high vibration and roll rate environments. A 15% performance improvement was observed in the simulation results when the preload charge level was reduced by 30%. Comparable performance improvement was also predicted by the MCSP studies when only the MESG calibration errors (gyro turn-on repeatability errors were eliminated) were used to drive the system. The MCSP results indicated that neither high vibration nor high roll rate and acceleration environments should prevent the MICRON system from achieving its specified navigation accuracy.

A covariance analysis computer program (to be used for statistical error propagation studies) was developed to supplement the MCSP and to increase the capability to simulate MICRON system performance. The derivation of the MICRON error equations was presented, the structure of the covariance analysis program described (see Fig. 10), and the

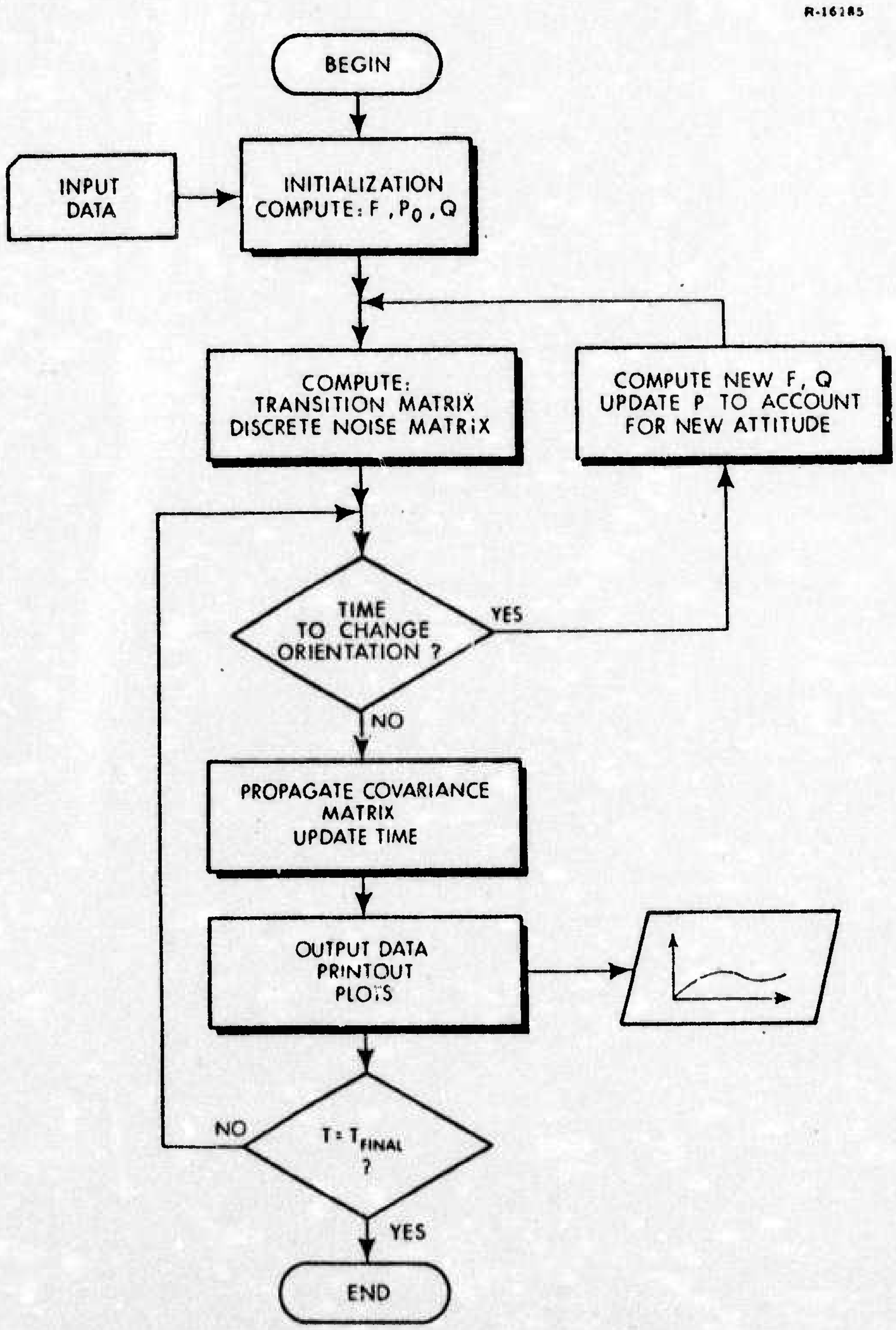

Figure 10 Flowchart for Error Analysis Computer Program

results of a brief investigation to determine the propagation characteristics of those error sources unique to MICRON were discussed. Because there is insufficient data available to allow development of valid statistical models describing residual MESG errors, it was assumed during the study that the errors were due to miscalibration of several of the drift rate and ARO error compensation coefficients. Figure 11, which is a typical output of the covariance analysis program, presents the rms navigation errors due to a 0.1 mrad rms calibration error in the x-scale factor attitude readout of the primary MESG.

It is strongly suggested that development of models to describe the residual MESG errors be given high priority during future MICRON Analysis studies since these models of the MICRON system are needed for use in modern data processing algorithms (e.g., Kalman filtering) which will combine MICRON data with the navigation aids that are available in a modern avionics suite. To aid in this effort, it was suggested that a Sensor Data Bank in which to store data collected on all MESG's that are manufactured be established. Residual error model determination is an iterative process during which test data is analyzed, models are postulated, and model predicted system performance is compared with test data. The covariance analysis program developed in this report will be a very useful tool in this effort.

In support of the N57A test program, TASC reviewed the Test Plan document and evaluated the test data collected. The review of the Test Plan suggested several areas where improvement could be made. In particular, with respect to the van test program, the following suggestions were made:

- Conduct long duration (6 to 8 hr) van runs.

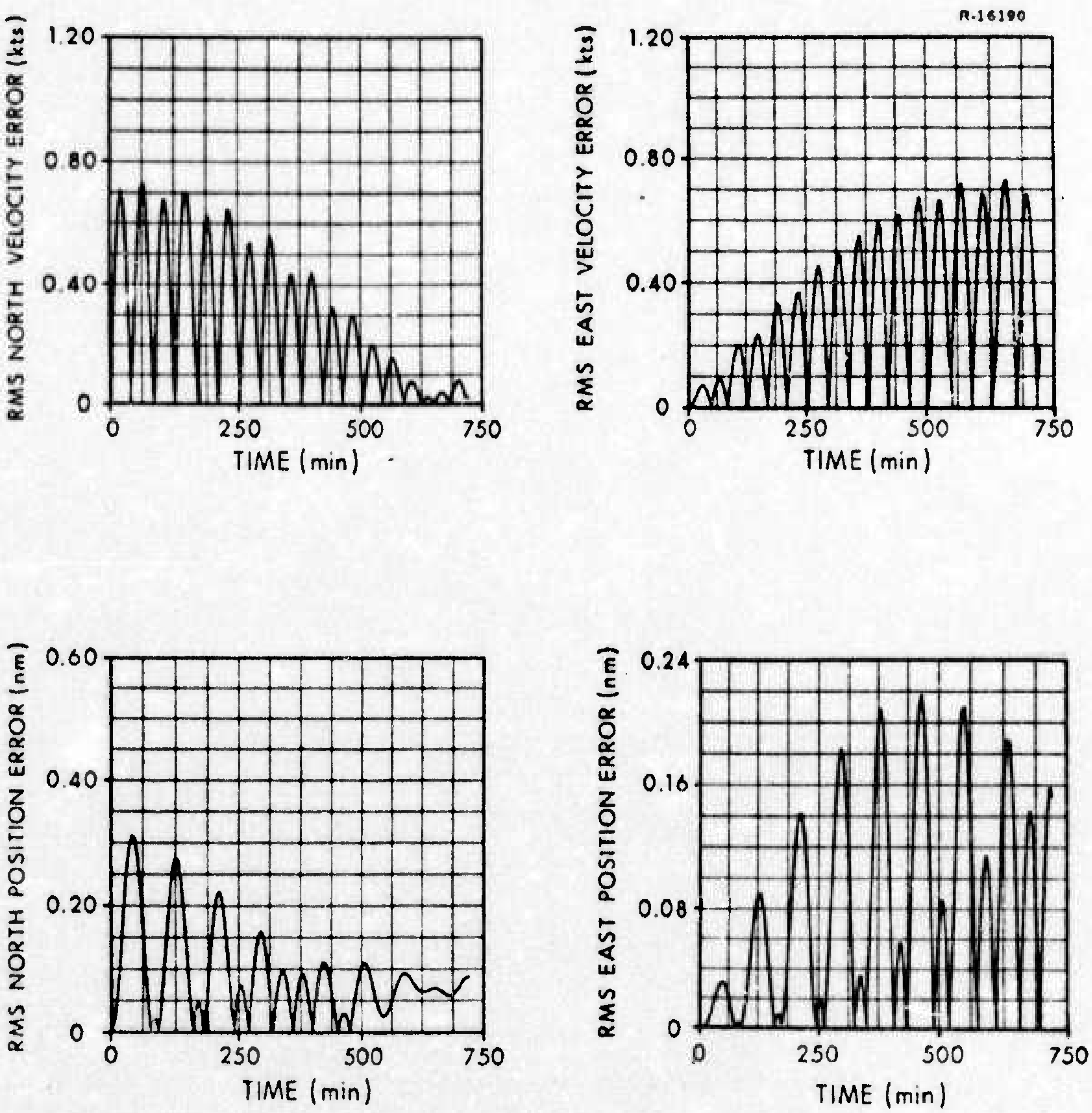

Figure 11 Navigation Errors Due to 0.1 mrad (rms) x-Scale Factor ARO Error in the Primary MESG

- Implement an altimeter and an active vertical channel.
- Provide a velocity reference in the van against which to evaluate N57A performance.
- Include significant altitude variations in the van test courses.

Many of these suggestions were adopted by Autonetics for the second set of van tests that were planned for the N57A.

Evaluation of the data collected during the N57A laboratory, environmental, and van test programs indicate that the observed system performance achieves most of the targets that were established for the system. The system accuracy that was computed based on all the tests performed was:

- radial error rate CEP = 0.87 nm/hr
- horizontal velocity error (1σ) = 3.2 ft/sec

None of the environments to which the N57A was subjected identified any significant performance deficiency, although vibration performance has not been completely verified due to test equipment problems. Those areas which have been identified by the results of the test program as requiring additional testing and development are reaction time and calibration stability.

A reevaluation of the MICRON design error budget should be conducted in light of the results of the N57A test program. Due to the lack of valid models to describe residual MESG errors, the design error budget apparently imposed unnecessarily severe specifications on MESG residual errors. (Although the observed system performance was consistent with the targets, the residual instrument errors were generally larger than the values allowed in the error budget.) Additional analytic effort will be required to resolve this issue and define a revised error budget for the final MICRON design.

4. LORAN/INERTIAL STUDY

This chapter describes the evaluation of Kalman filtering applied to an airborne Loran/Inertial weapon delivery system. As illustrated in Fig. 12 the basic elements of this system are an inertial measurement unit, a Loran receiver, and a computer which implements a Kalman filtering algorithm. The measurement is the difference between the inertial system indication of position and the Loran indication of position.* The difference is operated on by the Kalman filter to produce estimates of the inertial system position, velocity, and attitude errors and generally also to supply corrective signals to inertial platform and navigation algorithms. Properly designed, this configuration combines short-term inertial system stability with bounded Loran position errors to produce the required weapon delivery accuracy.

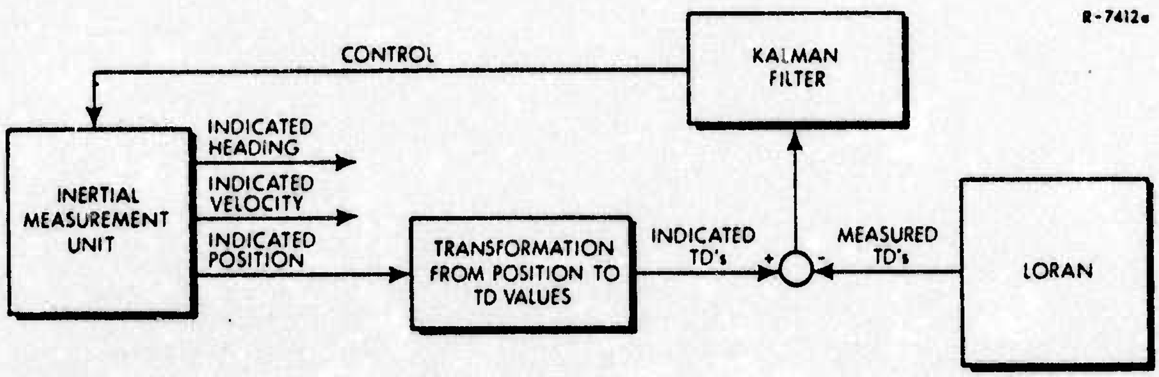

Figure 12 Typical Loran/Inertial Configuration

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*As shown in Fig. 12, this "position difference" is usually computed at the TDA, TDB level (where, for example, TDA is the Time Difference between the Master and Secondary A).

Reference 9 describes a study to evaluate an airborne Loran/Inertial weapon delivery system, the AN/ARN-101. In the study a covariance analysis of an optimal (59-state) Loran/Inertial Kalman filter and the proposed suboptimal Kalman filters of two competing vendors, Lear Siegler, Inc. (LSI) and International Telephone and Telegraph Avionics Division (ITT), were performed. Each vendor designed and developed his own Loran receiver, propagation prediction routine, weapon delivery algorithm and Kalman filter algorithm. In the study particular attention was given to the proposed Kalman filter designs, Due to the competitive-sensitive nature of this study only a summary of the optimal or baseline system performance is presented here. Full details of the optimal system performance analysis are available in the open literature (Ref. 10).

The covariance analysis simulation was designed to evaluate AN/ARN-101 flight testing. The simulated flight path and test parameters are given in Fig. 13 and Table 1, respectively. Performance predictions were generated in the form of rms error time histories, see Fig. 14, and system mean-squared error budgets, see Fig. 15. Similar results were generated for the vendor-proposed filter mechanizations. Additonally, detailed analytical critiques of each vendor design were performed.

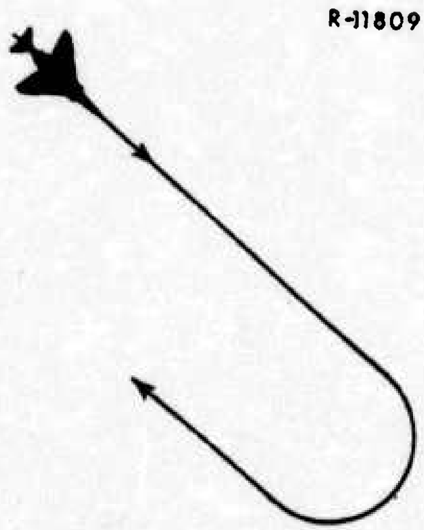


Figure 13   Flight Path for Covariance Simulations

TABLE 1

FLIGHT PARAMETERS FOR SIMULATION

Latitude	30.5°N (midflight)
Longitude	85°W (midflight)
Velocity	800 fps
Duration of flight	15 min { 10 min straight, level (about 80 nm) 30 sec turn 5 min straight, level
Turn radius	6667 ft
Acceleration in turn	3 g's
Altitude	5000 ft
Heading (initial)	135°
Bearings to transmitters:	
Master (Cape Fear)	45°
Secondary A (Jupiter)	135°
Secondary B (Dana)	350°

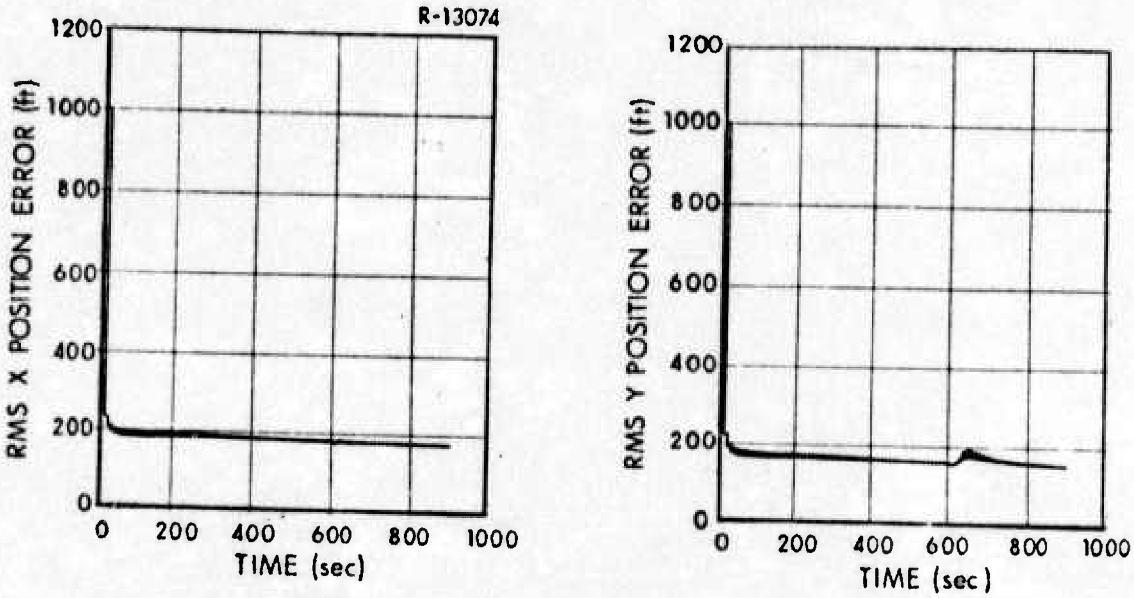


Figure 14 Optimal Loran/Inertial rms Position Error Time Histories

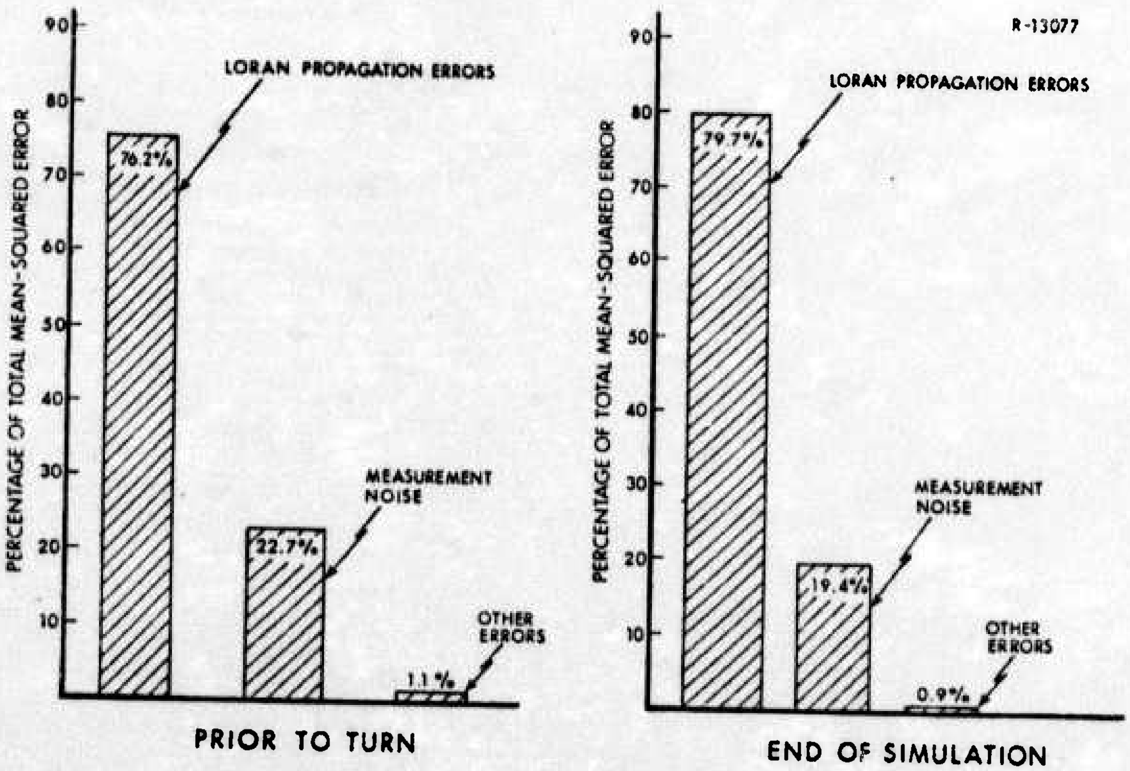


Figure 15 Optimal Loran/Inertial Y Position Error Budget

5. AERCAB STUDY

The USAF Advanced Escape and Rescue Capability (AERCAB) concept provides one approach to removing a crew member from a disabled aircraft and transporting him to a safe area where the chances of recovering him safely and quickly are markedly improved. With this concept, the ejection seat forms the basic structural element of an airframe which is equipped with propulsion, a lifting surface, and control surfaces for low-speed, low-altitude flight away from the area in which the "parent" aircraft was disabled.

In order to make best use of the AERCAB vehicle, it must be directed toward the safe area. This imposes three requirements on the vehicle:

- Ability to determine position relative to the safe area (Navigation);
- Ability to establish a suitable ground track and flight condition in order to reach the safe area (Guidance); and
- Ability to cause the vehicle to follow the desired flight path (Control).

In Ref. 11 the requirements and functional components of a fully automatic Guidance, Navigation, and Control (GN&C) System for the AERCAB vehicle have been evaluated, with particular attention devoted to guidance and control policies, navigation system characteristics, and total system costs. Navigation accuracies were determined for three flight ranges (50, 150, and 300 nm with safe areas of 25, 25, and 10,000 nm^2 respectively) and two flight speeds

(100 and 200 kt). The accuracies of the following navigation methods were evaluated:

Unaided Dead Reckoning

- Airspeed, Magnetic Compass
- Airspeed, Directional Gyroscope

Homing Navigation

- Airborne Direction Finder
- Ground-based Direction Finder (with Data Link)

Area Navigation

- VOR/DME (and TACAN)
- Multiple VOR
- Multiple DME
- Hyperbolic LORAN
- Direct-Ranging LORAN
- OMEGA
- Satellite

It has been determined that unaided dead reckoning (using airspeed and magnetic compass), airborne direction finding, and hyperbolic LORAN are the most feasible methods of navigation for AERCAB, and they represent a practical range of tradeoffs between simplicity and overall system performance. Systems based on these methods of navigation have been evaluated for cost, size, and weight.

In addition, increments for beacon/command receiver capability and various levels of stability augmentation have been considered.

The following conclusions were reached:

- Conventional approaches to vehicle control, as depicted in Fig. 16, should be adequate for the AERCAB mission, provided that the basic airframe is stable and that the transition to cruising flight (following ejection) is inherent in the deployment sequence and vehicle design.

- Energy management concepts can be used to identify simple vertical flight profiles (see Fig. 17) which increase the probability of successful crew retrieval by hastening the departure from the ejection area, conserving fuel, and avoiding terrain obstacles.

- Unaided dead reckoning navigation (using airspeed and magnetic heading alone) can be employed in the long-range flight (300 nm) if initial wind speed and the heading and range to the safe area can be identified. This form of navigation is not adequate for the shorter ranges, as the safe areas are a smaller percentage of flight range than in the long-range case.

- The addition of a line-of-sight homing device in the safe area allows a successful two-phase path to be flown in all cases (dead reckoning until acquiring the homing signal). The longer range of an airborne direction finder is desirable, but the "dog-leg" path which results from flying a constant heading, acquiring a homing signal, and revising flight direction degrades performance, and an active device in the safe area can be detected by hostile forces.

- Homing or beacon/command link techniques also can be employed in cooperation with special tracking or "buddy" aircraft.

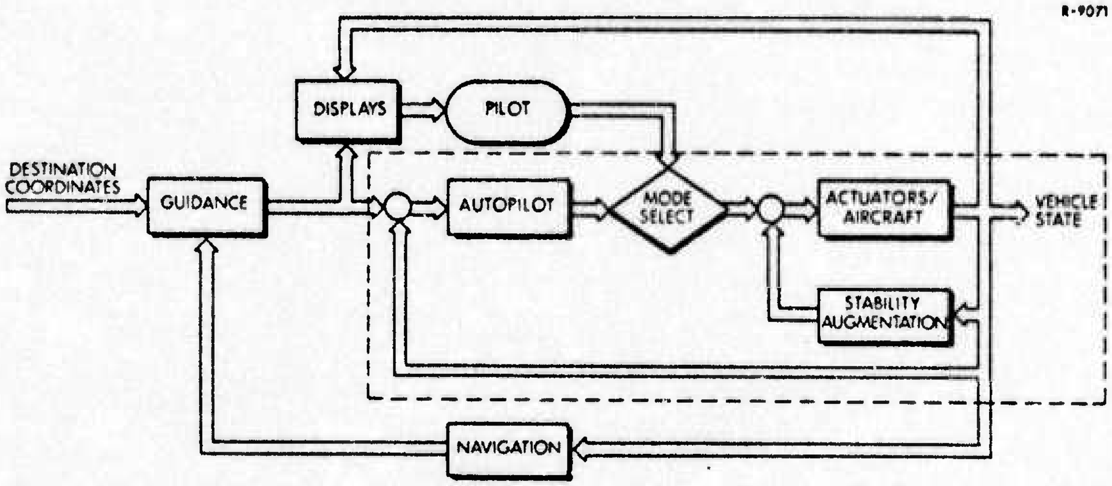


Figure 16 Functional Layout of the AERCAB Guidance, Navigation, and Control System

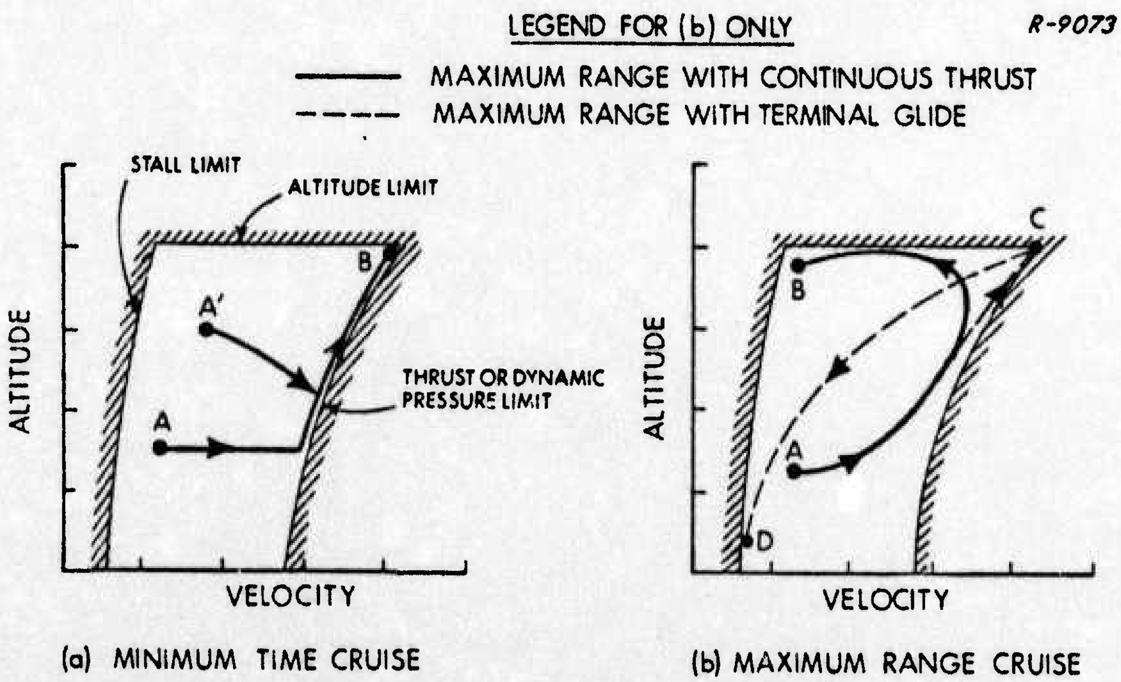


Figure 17 AERCAB Vertical Guidance Policies

- Of the several area navigation methods which can be considered, hyperbolic LORAN provides the most feasible solution for the AERCAB system. Accuracy of this system is acceptable at all flight ranges, cost of on-board equipment is modest, identification of the safe area is secure, and the system is compatible with existing military navigation networks and procedures.

Development cost estimates for the AERCAB GN&C system ranged from $490,000 for unaided dead reckoning using analog computation to $1,100,000 for digital LORAN navigation, while unit procurement costs (in 500-unit lots) were estimated at $4,400 to $14,600. (All costs are in 1973 dollars.) GN&C system weights were estimated to vary between 36 and 59 lb, while size estimates ranged from 480 to 1060 cu.in. The estimates were based on component sizes and weights; hence, repackaging of the integrated system could lead to size and weight reductions.

It was concluded that an automatic Guidance, Navigation, and Control System for the AERCAB vehicle is not only feasible, but that it improves the probability of successful crew retrieval by easing the workload of a possibly injured pilot, by optimizing the flight performance of the vehicle, and by providing navigation to a safe area.

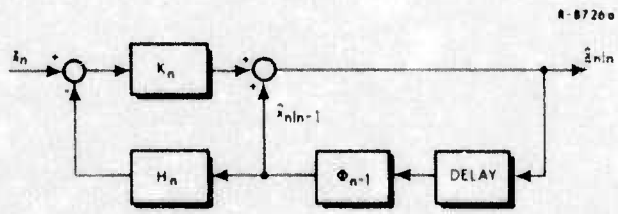
6. REDUCED-ORDER ESTIMATORS

A high-performance aircraft navigation system requires a data processing algorithm to mix data from an inertial system and external navigation aids. The Kalman filter has gained wide acceptance as the best algorithm for this type of system integration. In fact, many Air Force systems rely on the Kalman filter to achieve high navigation accuracy.

However, the Kalman filter has two serious problems which limit its usefulness as a system integration algorithm:

- Implementation of the Kalman filter for high-order dynamic systems requires a very large airborne computer.
- The performance of the Kalman filter is highly dependent on the validity of the system model used in its design.

Some insight into possible solutions to these problems is provided by studying the block diagram of the Kalman filter. Figure 18 shows the Kalman filter block



H_n = MEASUREMENT MATRIX AT TIME n

K_n = GAIN ON NEW INFORMATION IN ESTIMATOR

$\hat{x}_{n|n-1}$ = ONE-STEP PREDICTION OF THE STATE OF A LINEAR SYSTEM AT TIME $n-1$.

$\hat{x}_{n|n}$ = ESTIMATE OF THE STATE OF A LINEAR SYSTEM BASED ON z_k, $k = 0, 1, 2, \ldots, n$.

z_n = MEASUREMENTS AT TIME n

Φ_{n-1} = STATE TRANSITION MATRIX AT TIME $n-1$

Figure 18 Conventional Kalman Filter Block Diagram

diagram in its conventional form. In Figure 19 this block diagram has been redrawn to emphasize the relationship between the use of current measurements and a memory of past

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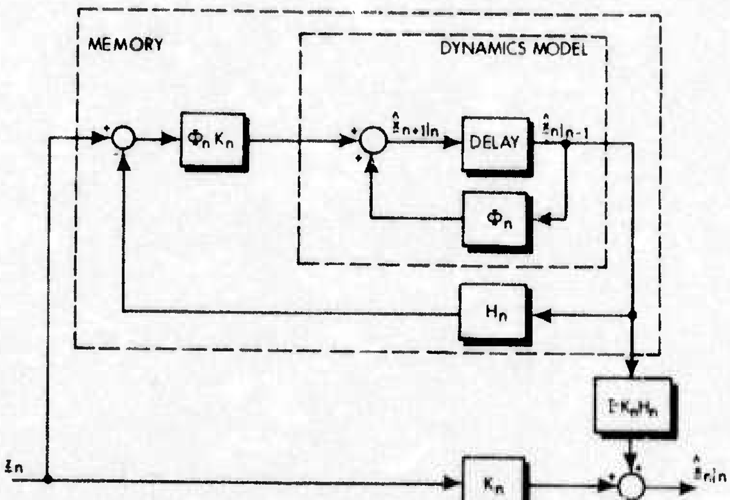

H_n = MEASUREMENT MATRIX AT TIME n
I = IDENTITY MATRIX
K_n = GAIN ON NEW INFORMATION IN ESTIMATOR
$\hat{x}_{n|n-1}$ = ONE STEP PREDICTION OF THE STATE OF A LINEAR SYSTEM AT TIME n-1.
$\hat{x}_{n|n}$ = ESTIMATE OF THE STATE OF A LINEAR SYSTEM BASED ON z_k, k = 0, 1, 2,...., n.
z_n = MEASUREMENTS AT TIME n
Φ_{n-1} = STATE TRANSITION MATRIX AT TIME n-1.

Figure 19 Alternative Kalman Filter Block Diagram

measurements. In Fig. 20 the block diagram is simplified to emphasize this relationship. Note that the Kalman filter consists of a dynamic system, which acts as a memory of past measurements, and a memoryless linear system, which mixes the measurements and the memory states to produce a set of estimates. It does not usually make sense to discard current measurements, but it is reasonable to consider reducing the order of the dynamic system used for the memory. Data processing algorithms which fit the block diagram of Fig. 20 but have a lower-order memory than the Kalman filter will be referred to here as reduced-order estimators. Obviously,

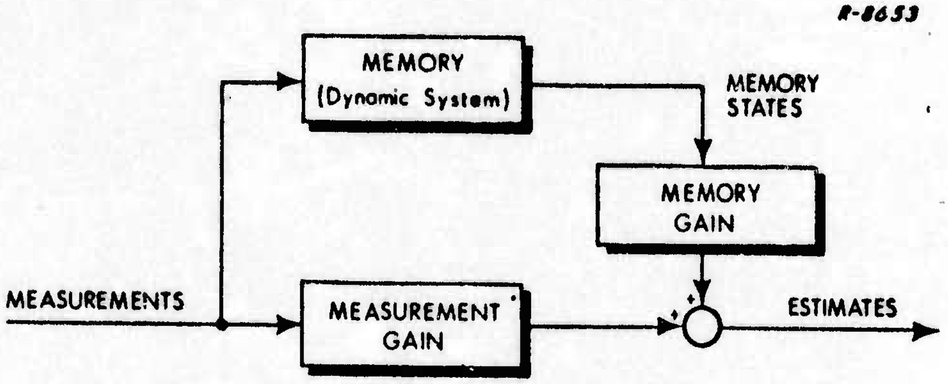

Figure 20   Simplified Block Diagram of the Kalman Filter

the implementation of a reduced-order estimator can be much less complex than that of the Kalman filter. Therefore, it may be possible to significantly relax the airborne computer requirements if a reduced-order estimator is used.

Furthermore, the performance of a reduced-order estimator has been found to be less dependent on the system model used in its design. A reduced-order estimator is much less dependent on its memory and more readily accepts new measurements. Therefore, it does not depend as heavily on its system model.

Reference 12 reports original work relating to the systematic design of reduced-order estimators. Equations are presented which provide the optimum estimator parameters once a particular set of states has been chosen. The resulting estimator minimizes the variance of the estimation error subject to the constraints on estimator complexity. In other words, the minimum-variance reduced-order (MVRO) estimator takes maximum advantage of the available observations subject to the constraints imposed on the estimator.

The principal significance of MVRO estimators is their value as an aid in the design of practical reduced-order filters. Although the equations for the optimum estimator parameters may be too complex to implement in real time, the MVRO estimators provide a quantitative criterion for evaluating the performance of a practical reduced-order estimator. Thus, study of minimum-variance reduced-order estimators provides a filter designer with the information necessary to decide how much performance to sacrifice for mechanization simplicity. As depicted in Fig. 21 a MVRO analysis provides a performance target for suboptimal filter design. Additionally, MVRO estimators provide

- Guidelines for choosing the parameters of a reduced-order estimator.
- An indication of which states should be selected for the reduced-order estimator.

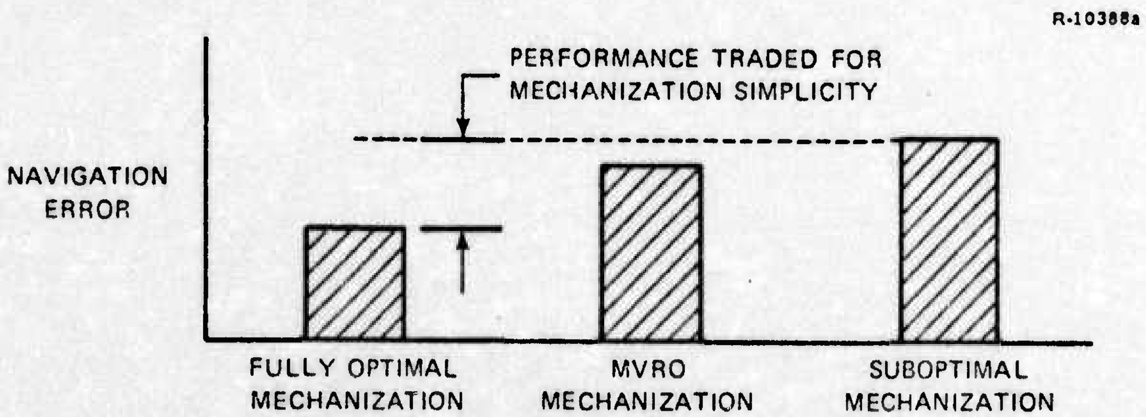

Figure 21 Performance Goal in Suboptimal Filter Design

A hybrid aircraft navigation example was formulated and used to compare the performance of a heuristically-designed suboptimal reduced-order filter with that of the

MVRO estimator and the fully-optimal Kalman filter (Ref. 12). The three columns in Table 2 correspond to the three categories represented in Fig. 21. In this example, the heuristically-designed filter was considerably inferior to the 18-state MVRO (see shaded comparisons). This indicates that additional design effort to improve the filter performance may be warranted. In other cases, where the heuristic and MVRO filter produce more comparable performance (say, 10 to 20% difference in system errors), additional filter design effort would probably not be worthwhile. This illustrates the values of the MVRO as a guideline in the design of practical filters.

TABLE 2

ESTIMATOR PERFORMANCE COMPARISON

ERROR STATE	UNITS	33-STATE OPTIMAL	18-STATE MVRO	18-STATE SUBOPTIMAL
ϕ_z	$\widehat{min}$	0.43	0.45	0.80
δR_N	ft	9.7	12.0	15.1
δR_E	ft	8.6	9.3	13.7
δh	ft	12.2	12.6	15.5
$\lvert\delta R\rvert$	ft	17.8	19.7	25.6
δV_N	ft/sec	0.08	0.14	0.15
δV_E	ft/sec	0.08	0.10	0.15
δV_Z	ft/sec	0.14	0.18	0.36
$\lvert\delta V\rvert$		0.18	0.25	0.42
δT_1	ft	9.7	10.1	11.8
$\delta \dot{T}_1$	ft/sec	0.020	0.021	0.035

7. MODULAR ESTIMATORS

A hybrid aircraft navigation system processes data from a variety of sensors to produce estimates of the aircraft's attitude, position, and velocity. These estimates of the aircraft's state are displayed to the pilot and used by the aircraft's automatic control systems. A typical hybrid navigation system is illustrated in Fig. 22.

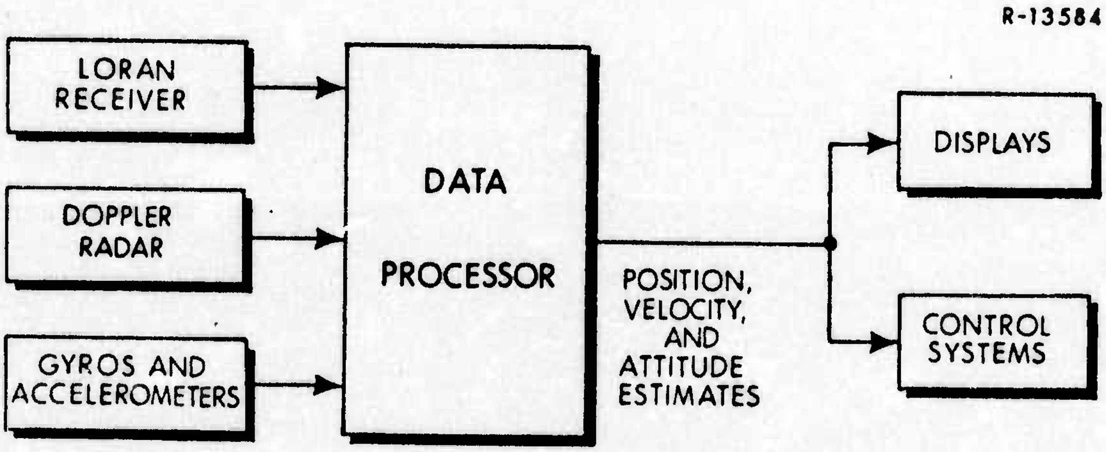

Figure 22 Typical Hybrid Navigation System Structure

Theoretically, the most accurate estimates of the system states would be produced by a single data processor operating on all the raw sensor data simultaneously. However, such a centralized estimation architecture requires communication of large quantities of information to a central computer. Furthermore, an extremely fast central computer is needed to process all of the raw data at sensor data rates. Since the cost of a communications channel increases with bandwidth and the cost of a computer increases with speed,

a centralized estimation system can become quite costly. Also, a centralized estimation architecture is not conducive to a modular system design since a change in one of the sensors can impact the design of the entire system.

Fortunately, an attractive alternative to the centralized estimation architecture is now available. Recent advances in large scale integration (LSI) electronics have made data processing units available which are physically small, lightweight, cheap, and low in power consumption. Thus, it is feasible to consider modular estimation architectures which perform relatively sophisticated data preprocessing within each sensor package, as illustrated in Fig. 23.

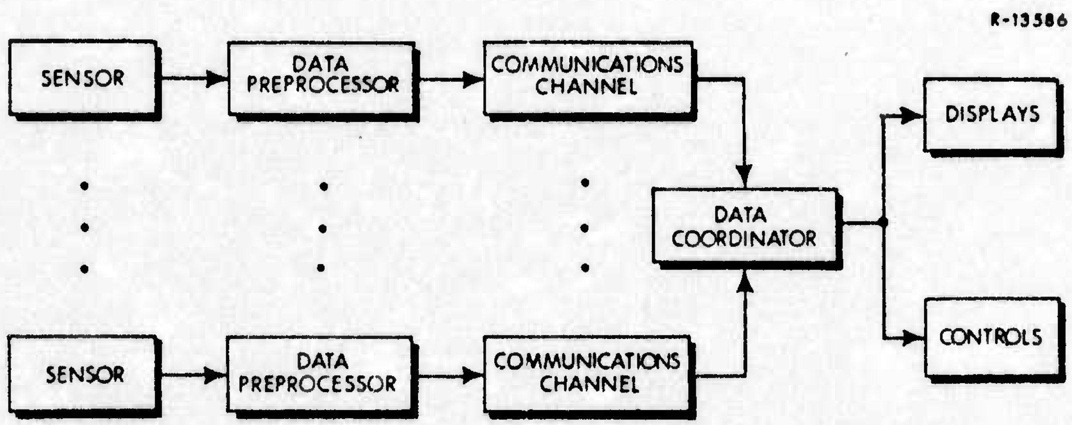

Figure 23 Modular Estimation Architecture

In this modular estimation architecture, data preprocessors are operated at sensor data rates to remove redundancy in the sensor data. The resulting compressed information is transmitted at a slower rate to a data coordinator, which supplies estimates to the displays and controls.

Modular estimators offer advantages in each of the following areas:

(1) Computer Capacity - Data preprocessors operate in parallel with the data coordinator. This increases the computational capacity of the system without requiring an increase in the speed of the data coordinator.

(2) Executive Program Complexity - Since data can be stored in the preprocessors, many of the complex timing problems and executive interrupt structures usually associated with real-time data processing can be avoided.

(3) Channel Capacity - Since data compression occurs at the sensors, the capacity required for the communication channels feeding the data coordinator can be greatly reduced.

(4) Modularity and Flexibility - The interfaces between the data coordinator and certain functional types of sensor/preprocessor packages can be fixed. Thus, a velocity reference could replace any other velocity reference without affecting the electrical and mechanical design of any other part of the system.

(5) System Reliability - Preprocessors can be designed in such a way that a failure of a single component will still leave the system operational.

Actually, state-of-the-art navigation systems already use a form of modular estimation. A typical state-of-the-art navigation system, diagrammed in Fig. 24, preprocesses accelerometer and gyro measurements by implementing a set of equations, called mechanization equations, to produce position, velocity, and attitude estimates. Signals from radio navigation aids are also preprocessed by signal detection and demodulation techniques, which serve to compress the data so that information not required for navigation is removed and relevant information is retained. Although these preprocessing equations are generally nonlinear, the errors

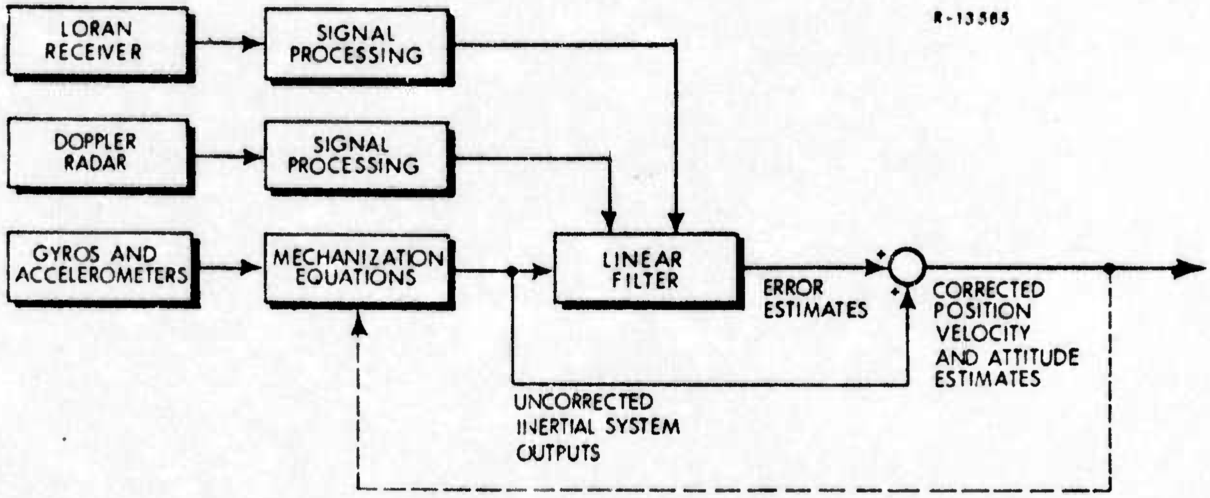

Figure 24 Typical State-of-the-Art Navigation System

in the resulting compressed data can usually be modeled as the outputs of a linear system driven by Gaussian noise. Therefore, a linear filter can be used to coordinate the compressed sensor data and determine the minimum-variance estimates of the navigation system errors. These error estimates are then used to correct the inertial system outputs, and the corrected output may be used to reset the mechanization equations.

Reference 13 reports original work which establishes the mathematical foundations for a systematic modular-estimator design procedure, consisting of the following steps:

(1) Either heuristic or Minimum-Variance Reduced-Order (MVRO, developed in Ref. 12) design procedures are used to design the algorithms for the data preprocessors.

(2) The performance of each data preprocessor is evaluated by comparing its rate distortion curve with the rate distortion curve of the system/sensor combination. Methods of computing these rate distortion curves are derived in Ref. 13.

(3) Either heuristic or MVRO design procedures are used to design the data coordinator which converts the compressed data to a state estimate.

(4) Sensitivity analysis techniques are used to evaluate the performance of the complete modular estimator and its performance is compared to that of the Kalman filter which, alternatively, could process the raw sensor data. (The sensitivity analysis techniques required to evaluate the performance of the complete modular estimator are also discussed in Ref. 13.)

An example is presented to illustrate preprocessor design procedures. The preprocessor used in this example is the optimum preprocessor which takes the form shown in Fig. 25. A Differential Pulse Code Modulation (DPCM) System (Fig. 26) is used to transmit the prefilter state to the data coordinator. The details of the design of the DPCM system are also presented in Ref. 13.

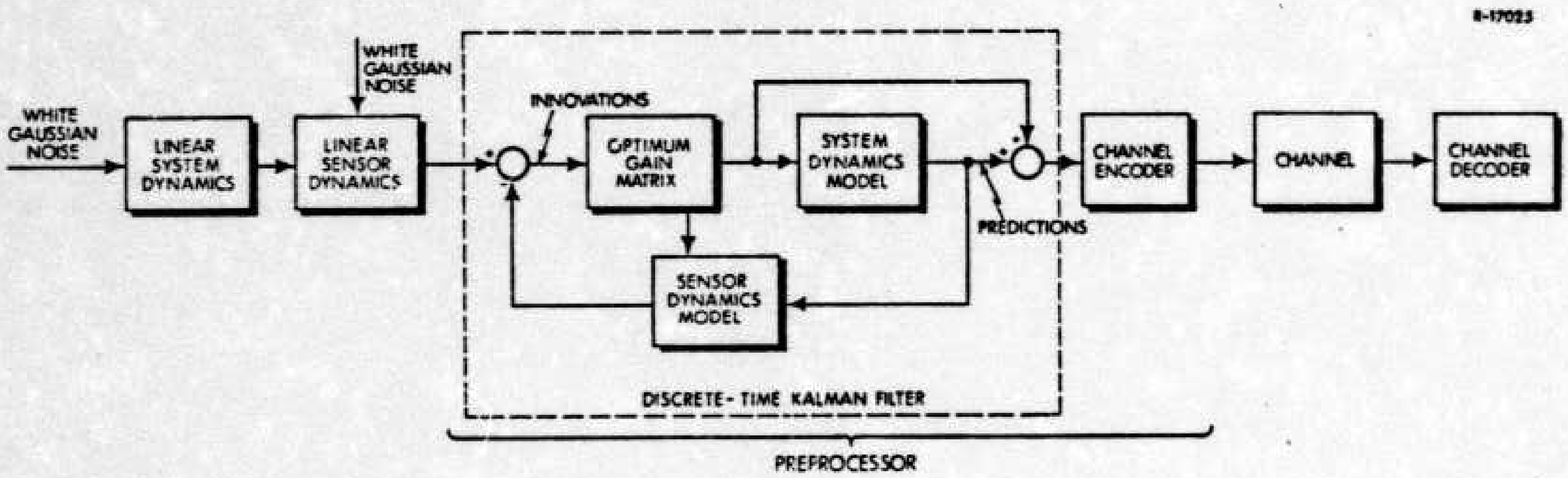

Figure 25 Optimum Preprocessor for Gaussian Signals

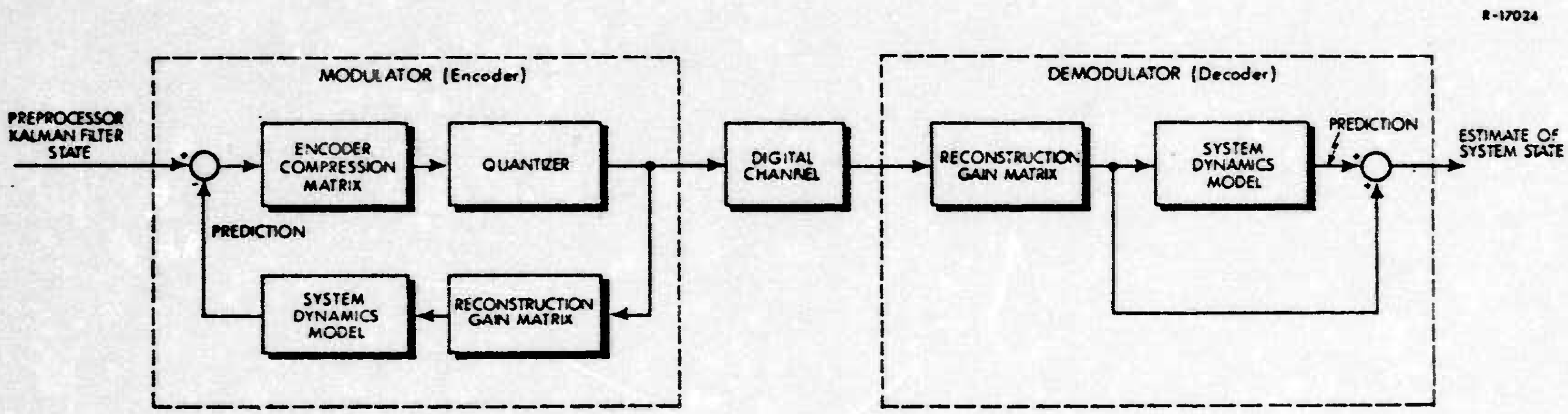

Figure 26 Differential Pulse Code Modulation-Demodulation System

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